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During the DARPA ANNT Program contract, new neural network architectures were developed to carry out autonomous real-time preprocessing, segmentation, recognition, timing, and control of both spatial and temporal inputs. These architectures contribute to: (1) preprocessing of visual form and motion signals; (2) preprocessing of acoustic signals; (3) adaptive pattern recognition and categorization in an unsupervised learning context; (4) adaptive pattern recognition and prediction in a supervised learning context; (5) processing of temporal patterns using working memory networks, with applications to 3-D object recognition; (6) adaptive timing for task scheduling; (7) adaptive sensory-motor control using head-centered spatial representations of 3-D target position.

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DARPA FINAL TECHNICAL REPORT

October 1, 1989—December 31, 1992

DEVELOPMENT OF NEURAL NETWORK ARCHITECTURES FOR SELF-ORGANIZING PATTERN RECOGNITION AND ROBOTICS

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Artificial Neural Network Technology (ANNT) Program: Theory and Modeling

DARPA Final Technical Report

Development of Neural Network Architectures for Self-Organizing Pattern Recognition and Robotics

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Boston University

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PUBLICATIONS PARTIALLY SUPPORTED BY DARPA CONTRACT AFOSR-90-0083

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Development of Neural Network Architectures
for Self-Organizing Pattern Recognition and Robotics

Contract AFOSR 90-0083

Principal Investigators:
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SUMMARY

During the DARPA ANNT Program contract, new neural network architectures were developed to carry out autonomous real-time preprocessing, segmentation, recognition, timing, and control of both spatial and temporal inputs. This brief summary is followed by a more extensive one, which cites articles from the list of publications (pp. 1-6).

(1) Preprocessing of visual form and motion signals: Parallel cortical systems for the processing of static visual forms and moving visual forms are derived from a principle called FM Symmetry. A solution of the global motion segmentation problem for computer vision is also outlined, as well as an analysis of 3-D vision and figure-ground pop-out (FACADE theory). A feedforward What-and-Where filter models parallel visual systems to generate an input representation (What it is) that is invariant to position, size, and orientation without discarding this information (Where it is). Synchronized oscillations in a model of visual cortex are capable of rapidly binding spatially distributed feature detectors into a globally coherent segmentation. Another system separates scenic figures from each other and a cluttered background. The vision models have been applied to the analysis of brightness perception, illusory contours, feature binding, and reset. The models have also been applied to the processing of synthetic aperture radar (SAR) images.

(2) Preprocessing of acoustic signals: A neural network model for preprocessing an acoustic source generates a representation of pitch as a spatial pattern that emerges from a type of neural harmonic sieve. Neural networks are also used to evaluate 160 speaker normalization methods for vowel recognition.

(3) Adaptive pattern recognition and categorization: Unsupervised learning: An algorithmic learning system, called ART2-A, achieves a 2-3 order of magnitude speed-up over the ART 2 recognition system. Another new analog adaptive resonance model (fuzzy ART) incorporates computations from fuzzy set theory into the binary ART 1 model. When used as part of a larger architecture for supervised learning, fuzzy ART enables the user to interpret vectors of learned adaptive weights as if-then rules, thus defining a self-organizing expert system. ART systems are also central to a neural theory of visual search and attention to segmentations; and to an analysis of normal and amnesic learning.

(4) Adaptive pattern recognition and prediction: Supervised learning: The ARTMAP and fuzzy ARTMAP architectures carry out incremental supervised learning of recognition categories and multidimensional maps in response to arbitrary sequences of analog or binary vectors. A Minimax Learning Rule conjointly minimizes predictive error and maximizes code compression, thereby optimally shaping recognition categories to the statistics of the input environment. Benchmark studies affirm ARTMAP's power compared to alternative models from machine learning, genetic algorithms, and neural networks, including application domains such as large database analysis, medical prediction, rule extraction, and probability estimation. Fusion ARTMAP is a multi-channel ARTMAP network for multi-sensor data fusion. Another system (NEXsT) uses VLSI switching theory to design

neural networks with a minimum number of if-then rules for binary supervised learning problems.

(5) Temporal patterns, working memory, and 3-D object recognition: Working memory neural networks, called Sustained Temporal Order REcurrent (STORE) models, encode the invariant temporal order of sequential events, with repeated or non-repeated items, in a manner that is stable under incremental learning conditions. Another system, ART-EMAP, uses spatial and temporal evidence accumulation to improve ARTMAP performance in noisy input environments. Both STORE and ART-EMAP systems are being applied to 3-D object recognition problems.

(6) Adaptive timing: A neural network circuit models adaptive timing of recognition and reinforcement learning. The model is closely linked to circuits in the hippocampus.

(7) Adaptive control: An unsupervised error-based learning system called a Vector Associative Map (VAM) learns 3-D spatial representations and self-calibrating trajectory controllers in robotics applications. A model of sensory-motor control shows how outflow eye movement commands can be transformed by two stages of opponent processing into a head-centered spatial representation of 3-D target position. Opponent processing is again a key element in an analysis of arm movement data. Analysis of sensory-motor control systems frames a model of cerebellar learning. A model of motor oscillations simulates bimanual coordination and human and quadruped gait transitions. Another system models handwriting production, including cursive script. Related model properties are used in an application to optimal control of machine set-up scheduling.

These and related projects, including model development, analysis, simulation, and comparisons with behavioral and neural data, are described below.

The contract has provided partial summer salary for the two Principal Investigators and suppor for four Research Assistants, all of whom are PhD students in the Boston University Department of Cognitive and Neural Systems.

1. PREPROCESSING OF VISUAL FORM AND MOTION SIGNALS

(1A) Why do parallel cortical systems exist for the perception of static form and moving form?

This project analyses computational properties that clarify why the parallel cortical systems $V1-V2$, $V1-MT$, and $V1-V2-MT$ exist for the perceptual processing of static visual forms and moving visual forms. A symmetry principle, called FM Symmetry, is predicted to govern the development of these parallel cortical systems by computing all possible ways of symmetrically gating sustained cells with transient cells and organizing these sustained-transient cells into opponent pairs of on-cells and off-cells whose output signals are insensitive to direction-of-contrast. This symmetric organization explains how the static form system (Static BCS) generates emergent boundary segmentations whose outputs are insensitive to direction-of-contrast and insensitive to direction-of-motion, whereas the motion form system (Motion BCS) generates emergent boundary segmentations whose outputs are insensitive to direction-of-contrast but sensitive to direction-of-motion. FM Symmetry clarifies why the geometries of static and motion form perception differ; for example, why the opposite orientation of vertical is horizontal (90°), but the opposite direction of up is down (180°). Opposite orientations and directions are embedded in gated dipole opponent processes that are capable of antagonistic rebound. Negative afterimages, such as the MacKay and waterfall illusions, are hereby explained, as are aftereffects of long-range apparent motion. These antagonistic rebounds help to control a dynamic balance between complementary perceptual states of resonance and reset. Resonance cooperatively links features into emergent boundary segmentations via positive feedback in a CC Loop, and reset terminates a resonance when the image changes, thereby preventing massive smearing of percepts. These complementary preattentive states of resonance and reset are related to analogous states that govern attentive feature integration, learning, and memory search in Adaptive Resonance Theory. The mechanism used in the $V1-MT$ system to generate a wave of apparent motion between discrete flashes may also be used in other cortical systems to generate spatial shifts of attention. The theory suggests how the $V1-V2-MT$ cortical stream helps to compute moving-form-in-depth and how long-range apparent motion of illusory contours occurs. These results collectively argue against vision theories that espouse independent processing modules. Instead, specialized subsystems interact to overcome computational uncertainties and complementary deficiencies, to cooperatively bind features into context-sensitive resonances, and to realize symmetry principles that are predicted to govern the development of visual cortex. [56–59, 61]

(1B) Cortical dynamics of visual motion perception: Short-range and long-range apparent motion

The theory of biological motion perception is also used to explain classical and recent data about short-range and long-range apparent motion percepts that have not yet been explained by alternative models. These data include beta motion; split motion; gamma motion and reverse-contrast gamma motion; delta motion; visual inertia; the transition from group motion to element motion in response to a Ternus display as the interstimulus interval (ISI) decreases; group motion in response to a reverse-contrast Ternus display even at short ISIs; speed-up of motion velocity as interflash distance increases or flash duration decreases; dependence of the transition from element motion to group motion on stimulus duration and size; various classical dependencies between flash duration, spatial separation, ISI, and motion threshold known as Korte's Laws; dependence of motion strength on stimulus orientation and spatial frequency; short-range and long-range form-color interactions; and binocular interactions of flashes to different eyes. [68–69]

(1C) Neural dynamics of global motion segmentation: Detection fields, apertures, and resonant grouping

This project has developed a neural network model of global motion segmentation by visual cortex. Called the Motion *Boundary Contour System* (BCS), the model clarifies how ambiguous local movements on a complex moving shape are actively reorganized into a coherent global motion signal. Unlike many previous researchers, we analyse how a coherent motion signal is imparted to all regions of a moving figure, not only to regions at which unambiguous motion signals exist. The model hereby suggests a solution to the global aperture problem. The Motion BCS describes how preprocessing of motion signals by a Motion Oriented Contrast Filter (MOC Filter) is joined to long-range cooperative grouping mechanisms in a Motion Cooperative-Competitive Loop (MOCC Loop) to control phenomena such as motion capture and induced motion. The Motion BCS is computed in parallel with the Static BCS of Grossberg and Mingolla (1985a, 1985b, 1987). Homologous properties of the Motion BCS and the Static BCS, specialized to process movement directions and static orientations, respectively, support a unified explanation of many data about static form perception and motion form perception that have heretofore been unexplained or treated separately. Predictions about microscopic computational differences of the parallel cortical streams $V1 - MT$ and $V1 - V2$ are made. The Motion BCS can compute motion directions that may be synthesized from multiple orientations with opposite directions-of-contrast. Interactions of model simple cells, complex cells, hypercomplex cells, and bipole cells are described, with special emphasis given to new functional roles (direction disambiguation, induced motion) for end stopping at multiple processing stages and to the dynamic interplay of spatially short-range and long-range interactions. [65-66]

(1D) Brightness perception, illusory contours, and corticogeniculate feedback

A neural network model of early visual processing offers an explanation of brightness effects often associated with *illusory contours*. *Top-down feedback from the model's analog* of visual cortical complex cells to model lateral geniculate nucleus (LGN) cells are used to enhance contrast at line ends and other areas of boundary discontinuity. The result is an increase in perceived brightness outside a dark line end, akin to what Kennedy (1979) termed "brightness buttons" in his analysis of visual illusions. When several lines form a suitable configuration, as in an Ehrenstein pattern, the perceptual effect of enhanced brightness can be quite strong. Model simulations show the *generation of brightness buttons*. With the LGN model cricuitry embedded in a larger model of preattentive vision, simulations using complex inputs show the interaction of the brightness buttons with real and illusory contours. [54]

(1E) A what-and-where neural network for invariant image preprocessing

The What-and-Where filter is a feedforward neural network for invariant image preprocessing that represents the position, orientation, and size of an image figure (where it is) in a multiplexed spatial map. This map is used to generate an invariant representation of the figure that is insensitive to position, orientation, and size for purposes of pattern recognition (what it is). A multiscale array of oriented filters, followed by competition between orientations and scales is used to define the Where filter. [23]

(1F) Figure-ground separation of connected scenic figures: Boundaries, filling-in, and opponent processing

A neural network model performs automatic parallel separation of connected scenic figures from one another and from their backgrounds. The model is part of a self-organizing architecture for invariant pattern recognition in a cluttered environment. The figure-ground separation process iterates operations from a Feature Contour System (FCS) and a Boundary Contour System (BCS). The FCS discounts the illuminant and fills-in surface properties, such as brightness and color, using the discounted signals. A key idea of the FBF network is to use filling-in for figure-ground separation. The BCS generates boundary segmentations that define the regions in which filling-in occurs. The BCS is modelled by a feedforward network, called the CORT-X 2 filter, that combines oriented receptive fields with rectifying, competitive, and cooperative interactions to detect, regularize, and complete boundaries in up to 50% analog noise. This filter combines complementary properties of large receptive fields and small receptive fields, and of on-cells and off-cells, to generate positionally more accurate and less noisy boundaries. Double opponent interactions of on-cells and off-cells facilitate separation of figures with incomplete CORT-X boundaries. The results clarify why an FBF network can rapidly separate figures that humans cannot separate during visual search tasks. [74–77]

(1G) Cortical dynamics of 3-D vision and figure-ground pop-out

A neural model, called FACADE Theory (Form-And-Color-And-DEpth), shows how the parvocellular processing streams from LGN to V4 can give rise to 3-D visual percepts in which figures pop-out from their backgrounds. The model suggests how cortical mechanisms such as boundary completion, texture segregation, and surface filling-in are used for this purpose. It clarifies how monocularly viewed parts of an image may fill-in the appropriate surface depth from contiguous binocularly viewed parts during DaVinci stereopsis. Other explanations include how a 2-D image may generate a 3-D percept, how spatially sparse disparity cues can generate continuous surface representations at different perceived depths, and how representations of occluded regions can be completed and recognized without usually being seen. The model has also been used to analyse data about such varied phenomena as illusory contours, shape-from-texture, visual persistence, and synchronous cortical oscillations. It suggests how the brain uses computationally complementary blob and interblob processing streams wherein a hierarchical resolution of uncertainty generates context-sensitive visual representations that overcome *several different* sources of local ambiguity in visual data. Cortical circuits of simple, complex, hypercomplex, and bipole cells are simulated. Recent psychophysical and neurobiological data relevant to model explanations and predictions are summarized. [60, 62]

(1H) Synchronized oscillations for binding spatially distributed feature codes into coherent spatial patterns

Neural network models are described for binding out-of-phase activations of spatially distributed cells into synchronized oscillations within a single processing cycle. These results suggest how the brain may overcome the temporal "jitter" inherent in multi-level processing of spatially distributed data. Coherent synchronous patterns of spatially distributed features are formed to represent and learn about external objects and events. Temporal jitter thus does not typically cause scenic parts to be combined into the wrong visual objects. During preattentive vision, such patterns may represent emergent boundary segmentations, including illusory contours. During attentive visual object recognition, such patterns may occur during an attentive resonant state that triggers new learning. Different properties of preattentive and attentive oscillations are predicted, and compared with neurophysiological data concerning rapid synchronization of cell activations in visual cortex. [70–73]

(1I) Cortical dynamics of feature binding and reset

Many properties of visual persistence are hypothesized to be caused by positive feedback in the visual cortical circuits that are responsible for the binding or segmentation of visual features into coherent visual forms, with the degree of persistence limited by circuits that reset these segmentations at stimulus offset. A model of the cortical local circuitry responsible for such feature binding and reset quantitatively simulates psychophysical data showing increase of persistence with spatial separation of a masking stimulus; inverse relation of persistence to flash luminance and duration; greater persistence of illusory contours than real contours, with maximal persistence at an intermediate stimulus duration; and dependence of persistence on pre-adapted stimulus orientation. Data concerning cortical cell responses to illusory and real contours are also analysed, as are alternative models of feature binding and persistence properties. [47–48]

(1J) Processing of synthetic aperture radar (SAR) images by the BCS/FCS system

An improved Boundary Contour System (BCS) and Feature Contour System (FCS) neural network model of preattentive vision has been applied to two large images containing range data gathered by a synthetic aperture radar (SAR) sensor. The goal of processing is to make structures such as motor vehicles, road, or buildings more salient and more interpretable to human observers than they are in the original imagery. Early processing by shunting center-surround networks compresses signal dynamic range and performs local contrast enhancement. Susequent processing by filters sensitive to oriented contrast, including short-range competition and long-range cooperation, segments the image into regions. Finally, a diffusive filling-in operation within the segmented regions produces coherent visible structures. The combination of BCS and FCS helps to locate and enhance structure over regions of many pixels, without the resulting blur characteristic of approaches based on low spatial frequency filtering alone. [46]

2. PREPROCESSING OF ACOUSTIC SIGNALS

(2A) A neural network model of pitch detection and representation

A neural network model capable of generating a spatial representation for the pitch of an acoustic source has been developed. The model, called the Spatial Pitch Network, uses a "harmonic sieve" mechanism whereby the strength of activation of a given pitch depends upon a weighted sum of narrow regions around the harmonics of the nominal pitch value. A key feature of the model is that higher harmonics contribute less to a pitch than lower ones. Suitably chosen harmonic weighting functions enable computer simulations of pitch perception data involving mistuned components, shifted harmonics, and various types of continuous spectra including rippled noise. It is shown how the weighting functions produce the dominance region and how they lead to octave shifts of pitch in response to ambiguous stimuli. No explicit attentional window is needed to limit pitch choices by the model. A method is described for relating the deterministic strength-of-activation pitch function to statistical human performance and for comparing the network model with Goldstein's statistical Optimum Processor Theory. [44-45]

(2B) Evaluation of speaker normalization methods for vowel recognition using fuzzy ARTMAP and K-NN

Fuzzy ARTMAP and K-Nearest Neighbor (K-NN) categorizers are used to evaluate intrinsic and extrinsic speaker normalization methods. Each classifier is trained on preprocessed, or normalized, vowel tokens from about 30% of the speakers of the Peterson-Barney database, then tested on data from the remaining speakers. Intrinsic normalization methods include one nonscaled, four psychophysical scales (bark, bark with end-correction, mel, ERB), and three log scales, each tested on four different combinations of the fundamental (F_0) and the formants (F_1, F_2, F_3). For each scale and frequency combination, four extrinsic speaker adaptation schemes are tested: centroid subtraction across all frequencies (CS), centroid subtraction for each frequency (CSi), linear scale (LS), and linear transformation (LT). A total of 32 intrinsic and 128 extrinsic methods are thus compared. Fuzzy ARTMAP and K-NN show similar trends, with K-NN performing somewhat better and fuzzy ARTMAP requiring about 1/10 as much memory. The optimal intrinsic normalization method is bark scale, or bark with end-correction, using the differences between all frequencies (Diff All). The order of performance for the extrinsic methods is LT, CSi, LS, and CS, with fuzzy ARTMAP performing best using bark scale with Diff All, and K-NN choosing psychophysical measures for all except CSi. [12]

3. ADAPTIVE PATTERN RECOGNITION AND CATEGORIZATION: UNSUPERVISED LEARNING

(3A) Fuzzy ART: Fast stable learning and categorization of analog patterns by an adaptive resonance system

A fuzzy Adaptive Resonance Theory (ART) model capable of rapid stable learning of recognition categories in response to arbitrary sequences of analog or binary input patterns has been developed. Fuzzy ART incorporates computations from fuzzy set theory into the ART 1 neural network, which learns to categorize only binary input patterns. The generalization to learning both analog and binary input patterns is achieved by replacing appearances of the intersection operator ($\cap$) in ART 1 by the MIN operator ($\wedge$) of fuzzy set theory. The MIN operator reduces to the intersection operator in the binary case. Category proliferation is prevented by normalizing input vectors at a preprocessing stage. A normalization procedure called complement coding leads to a symmetric theory in which the MIN operator ($\wedge$) and the MAX operator ($\vee$) of fuzzy set theory play complementary roles. Complement coding uses on-cells and off-cells to represent the input pattern, and preserves individual feature amplitudes while normalizing the total on-cell/off-cell vector. Learning is stable because all adaptive weights can only decrease in time. Decreasing weights correspond to increasing sizes of category "boxes". Smaller vigilance values lead to larger category boxes. Learning stops when the input space is covered by boxes. With fast learning and a finite input set of arbitrary size and composition, learning stabilizes after just one presentation of each input pattern. A fast-commit slow-recode option combines fast learning with a forgetting rule that buffers system memory against noise. Using this option, rare events can be rapidly learned, yet previously learned memories are not rapidly erased in response to statistically unreliable input fluctuations. [36–37]

(3B) ART 2-A: An adaptive resonance algorithm for rapid category learning and recognition

ART 2-A is an efficient algorithm that emulates the self-organizing pattern recognition and hypothesis testing properties of the ART 2 neural network architecture, but at a speed two to three orders of magnitude faster. Analysis and simulations show how the ART 2-A systems correspond to ART 2 dynamics at both the fast-learn limit and at intermediate learning rates. Intermediate learning rates permit fast commitment of category nodes but slow recoding, analogous to properties of word frequency effects, encoding specificity effects, and episodic memory. Better noise tolerance is hereby achieved without a loss of learning stability. The ART 2 and ART 2-A systems are contrasted with the leader algorithm. The speed of ART 2-A makes practical the use of ART 2 modules in large-scale neural computation. In particular, researchers using ART 2 for applications in the DARPA ANNT Program have used ART 2-A for their projects. [34–35]

(3C) A neural theory of visual search

A neural theory is proposed in which visual search is accomplished by perceptual grouping and segregation, which occurs simultaneously across the visual field, and object recognition, which is restricted to a selected region of the field. The theory offers an alternative hypothesis to recently developed variations on Feature Integration Theory (Treisman and Sato, 1991) and the Guided Search Model (Wolfe, Cave, and Franzel, 1989). A neural architecture and search algorithm is specified that quantitatively explains a wide range of psychophysical search data (Cohen and Ivry, 1991; Mordkoff, Yantis, and Egeth, 1990; Treisman and Sato, 1991; Wolfe, Cave, and Franzel, 1989). [67]

(3D) Normal and amnesic learning, recognition, and memory by a neural model of cortico-hippocampal interactions

The processes by which humans and other primates learn to recognize objects have been the subject of many models. Processes such as learning, categorization, attention, memory search, expectation, and novelty detection work together at different stages to realize object recognition. The structure and function of one such model class (Adaptive Resonance Theory, ART) are related to known neurological learning and memory processes, such as how inferotemporal cortex can recognize both specialized and abstract information, and how medial temporal amnesia may be caused by lesions in the hippocampal formation. The model also suggests how hippocampal and inferotemporal processing may be linked during recognition learning. [20]

4. ADAPTIVE PATTERN RECOGNITION AND PREDICTION: SUPERVISED LEARNING

(4A) ARTMAP: Supervised real-time learning and classification of nonstationary data by a self-organizing neural network

A neural network architecture, called ARTMAP, autonomously learns to classify arbitrarily many, arbitrarily ordered vectors into recognition categories based on predictive success. This supervised learning system is built up from a pair of Adaptive Resonance Theory modules (ART_a and ART_b) that are capable of self-organizing stable recognition categories in response to arbitrary sequences of input patterns. During training trials, the ART_a module receives a stream $\{\mathbf{a}^{(p)}\}$ of input patterns, and ART_b receives a stream $\{\mathbf{b}^{(p)}\}$ of input patterns, where $\mathbf{b}^{(p)}$ is the correct prediction given $\mathbf{a}^{(p)}$. These ART modules are linked by an associative learning network and an internal controller that ensures autonomous system operation in real time. During test trials, the remaining patterns $\mathbf{a}^{(p)}$ are presented without $\mathbf{b}^{(p)}$, and their predictions at ART_b are compared with $\mathbf{b}^{(p)}$. Tested on a benchmark machine learning database in both on-line and off-line simulations, the ARTMAP system learns orders of magnitude more quickly, efficiently, and accurately than alternative algorithms, and achieves 100% accuracy after training on less than half the input patterns in the database. It achieves these properties by using an internal controller that conjointly maximizes predictive generalization and minimizes predictive error by linking predictive success to category size on a trial-by-trial basis, using only local operations. This computation increases the vigilance parameter ρ_a of ART_a by the minimal amount needed to correct a predictive error at ART_b. ARTMAP is hereby a type of self-organizing expert system that calibrates the selectivity of its hypotheses based upon predictive success. As a result, rare but important events can be quickly and sharply distinguished even if they are similar to frequent events with different consequences. Because ARTMAP learning is self-stabilizing, it can continue learning one or more databases, without degrading its corpus of memories, until its full memory capacity is utilized. [28–32]

(4B) Fuzzy ARTMAP: A neural network architecture for incremental supervised learning of analog multidimensional maps

Fuzzy ARTMAP extends the capabilities of ARTMAP to carry out incremental supervised learning of recognition categories and multidimensional maps in response to arbitrary sequences of analog or binary input vectors. A normalization procedure called complement coding leads to a symmetric theory in which the AND operator ($\wedge$) and the OR operator ($\vee$) of fuzzy logic play complementary roles. Improved prediction is achieved by training the system several times using different orderings of the input set. This voting strategy can also be used to assign confidence estimates to competing predictions given small, noisy, or incomplete training sets. Four classes of simulations illustrate fuzzy ARTMAP performance as compared to benchmark back propagation and genetic algorithm systems. These simulations include (i) finding points inside vs. outside a circle; (ii) learning to tell two spirals apart; (iii) incremental approximation of a piecewise continuous function; and (iv) a letter recognition database. [19, 21, 24–27]

(4C) Fusion ARTMAP: A neural network architecture for multi-channel data fusion and classification

Fusion ARTMAP is a self-organizing neural network architecture for multi-channel, or multi-sensor, data fusion. Single-channel fusion ARTMAP is functionally equivalent to fuzzy ART during unsupervised learning and to fuzzy ARTMAP during supervised learning. The network has a symmetric organization such that each channel can be dynamically configured to serve either as a data input or a teaching input to the system. An ART module forms a compressed recognition code within each channel. These codes, in turn, become inputs to a single ART system that organizes the global recognition code. When a predictive error occurs, a process called parallel match tracking simultaneously raises vigilances in multiple ART modules until reset is triggered in one of them. Parallel match tracking hereby resets only that portion of the recognition code with the poorest match, or minimum predictive confidence. This internally controlled selective reset process is a type of credit assignment that creates a parsimoniously connected learned network. Fusion ARTMAP's multi-channel coding is illustrated by simulations of the Quadruped Mammal database. [1]

(4D) Comparative performance measures of fuzzy ARTMAP, learned vector quantization, and back propagation for handwritten character recognition

A simulation study compares the performance of fuzzy ARTMAP with that of learned vector quantization and back propagation on a handwritten character recognition task. Training with fuzzy ARTMAP to a fixed criterion uses many fewer epochs. Voting with fuzzy ARTMAP yields the highest recognition rates. [22]

(4E) Rule extraction by fuzzy ARTMAP

Knowledge, in the form of fuzzy rules, can be derived from a self-organizing supervised learning neural network called fuzzy ARTMAP. Rule extraction proceeds in two stages: pruning removes those recognition nodes whose confidence index falls below a selected threshold, and a quantization of continuous learned weights allows the final system state to be translated into a usable set of rules. Simulations on a medical prediction problem, the Pima Indian Diabetes (PID) database, illustrate the method. In the simulations, pruned networks about one-third the size of the original actually show improved performance. Quantization yields comprehensible rules with only slight degradation in test set prediction performance. [39]

(4F) Medical database analysis and survival prediction by neural networks

Fuzzy ARTMAP has been used for analysis of medical databases, with comparative studies of other neural networks and statistical methods. Survival prediction networks have been derived from large data sets for breast cancer, cardiac bypass surgery (CABG), and pneumonia patients. Ongoing studies focus on problems of missing data and rule identification. [11, 53]

(4G) Fuzzy ARTMAP, slow learning, and probability estimation

A nonparametric probability estimation procedure uses the fuzzy ARTMAP neural network. Because the procedure does not make *a priori* assumptions about underlying probability distributions, it yields accurate estimates on a wide variety of prediction tasks. Fuzzy ARTMAP is used to perform probability estimation in two different modes. In a "slow-learning" mode, input-output associations change slowly, with the strength of each association computing a conditional probability estimate. In "max-nodes" mode, a fixed number of categories are coded during an initial fast learning interval, and weights are then tuned by slow learning. Simulations illustrate system performance on tasks in which various numbers of clusters in the set of input vectors mapped to a given class. [33]

(4H) Probabilistic neural networks and calibration of supervised learning systems

Probabilistic, or general regression, neural networks have been developed for the calibration of supervised learning systems. A training process learns receptive field width parameters and calibrates predictions to reflect binary outcome probabilities. [79]

(4I) Construction of neural network expert systems using switching theory

This project introduces a new family of neural network architectures (NEXsT) that use switching theory to construct and train minimal neural network classification expert systems. The primary insight that leads to the use of switching theory is that the problem of minimizing the number of rules and the number of IF statements (antecedents) per rule in a neural network expert system can be recast into the problem of minimizing the number of digital gates and the number of connections between digital gates in a Very Large Scale Integrated (VLSI) circuit. Algorithms for minimizing the number of gates and the number of connections between gates in VLSI circuits are used, with some modification, to generate minimal neural network classification expert systems. The minimal set of rules that the neural network generates to perform a task are readily extractable from the network's weights and topology. Analysis and simulations on several databases illustrate the system's performance. [78]

5. TEMPORAL PATTERNS, WORKING MEMORY, AND 3-D OBJECT RECOGNITION

(5A) Working memory networks for learning temporal order with application to 3-D visual object recognition

Working memory neural networks, called Sustained Temporal Order REcurrent (STORE) models, encode the invariant temporal order of sequential events in short-term memory (STM). Inputs to the networks may be presented with widely differing growth rates, amplitudes, durations, and interstimulus intervals without altering the stored STM representation. The STORE temporal order code is designed to enable groupings of the stored events to be stably learned and remembered in real time, even as new events perturb the system. Such invariance and stability properties are needed in neural architectures which self-organize learned codes for variable-rate speech perception, sensory-motor planning, or 3-D visual object recognition. Using such a working memory, a self-organizing architecture for invariant 3-D visual object recognition is described. The new model is based on a model of Seibert and Waxman, which builds a 3-D representation of an object from a temporally ordered sequence of its 2-D aspect graphs. The new model, called an ARTSTORE model, consists of the following cascade of processing modules: Invariant Preprocessor → ART 2 → STORE Model → ART 2 → Outstar Network. [3–4]

(5B) Working memories for storage and recall of arbitrary temporal sequences

An extension of the STORE model encodes a working memory capable of storing and recalling arbitrary temporal sequences of events, including repeated items. The memory encodes the invariant temporal order of sequential events that may be presented at widely differing speeds, durations, and interstimulus intervals. This temporal order code is designed to enable all possible groupings of sequential events to be stably learned and remembered in real time, even as new events perturb the system. [5–6]

(5C) ART-EMAP: Learning and prediction with spatial and temporal evidence accumulation

ART-EMAP is a neural architecture that uses spatial and temporal evidence accumulation to extend the capabilities of fuzzy ARTMAP. ART-EMAP combines supervised and unsupervised learning and a medium-term memory process to accomplish stable pattern category recognition in a noisy input environment. The ART-EMAP system features (i) distributed pattern registration at a view category field; (ii) a decision criterion for mapping between view and object categories which can delay categorization of ambiguous objects and trigger an evidence accumulation process when faced with a low confidence prediction; (iii) a process that accumulates evidence at a medium-term memory (MTM) field; and (iv) an unsupervised learning algorithm to fine-tune performance after a limited initial period of supervised network training. ART-EMAP dynamics are illustrated with a benchmark simulation example. Applications include 3-D object recognition from a series of ambiguous 2-D views. [38]

6. ADAPTIVE TIMING

(6A) A neural network model of adaptively timed reinforcement learning and hippocampal dynamics

A new neural network models adaptively timed reinforcement learning. The adaptive timing circuit is suggested to exist in the hippocampus, and to involve convergence of dentate granule cells on CA3 pyramidal cells, and NMDA receptors. This circuit forms part of a model neural system for the coordinated control of recognition learning, reinforcement learning, and motor learning, whose properties clarify how an animal can learn to acquire a delayed reward. Behavioral and neural data are summarized in support of each processing stage of the system. The relevant anatomical sites are in thalamus, neocortex, hippocampus, hypothalamus, amygdala, and cerebellum. Cerebellar influences on motor learning are distinguished from hippocampal influences on adaptive timing of reinforcement learning. The model simulates how damage to the hippocampal formation disrupts adaptive timing, eliminates attentional blocking, and causes symptoms of medial temporal amnesia. Properties of learned expectations, attentional focussing, memory search, and orienting reactions to novel events are used to analyse the blocking and amnesia data. The model also suggests how normal acquisition of subcortical emotional conditioning can occur after cortical ablation, even though extinction of emotional conditioning is retarded by cortical ablation. The model simulates how increasing the duration of an unconditioned stimulus increases the amplitude of emotional conditioning, but does not change adaptive timing; and how an increase in the intensity of a conditioned stimulus "speeds up the clock," but an increase in the intensity of an unconditioned stimulus does not. Computer simulations of the model fit parametric conditioning data, including a Weber law property and an inverted U property. Both primary and secondary adaptively timed conditioning are simulated, as are data concerning conditioning using multiple interstimulus intervals (ISIs), gradually or abruptly changing ISIs, partial reinforcement, and multiple stimuli that lead to time-averaging of responses. Neurobiologically testable predictions are made to facilitate further tests of the model. [64]

7. ADAPTIVE CONTROL

(7A) Neural representations for sensory-motor control: Head-centered 3-D target positions from opponent eye commands

This project describes how corollary discharges from outflow eye movement commands can be transformed by two stages of opponent neural processing into a head-centered representation of 3-D target position. This representation implicitly defines a cyclopean coordinate system whose variables approximate the binocular vergence and spherical, horizontal, and vertical angles with respect to the observer's head. Various psychophysical data concerning binocular distance perception and reaching behavior are clarified by this representation. The representation provides a foundation for learning head-centered and body-centered invariant representations of both foveated and non-foveated 3-D target positions. It also enables a solution to be developed of the classical motor equivalence problem, whereby many different joint configurations of a redundant manipulator can all be used to realize a desired trajectory in 3-D space. [55]

(7B) Emergence of tri-phasic muscle activation from the nonlinear interactions of central and spinal neural network circuits

The origin of the tri-phasic burst pattern, observed in the EMGs of opponent muscles during rapid self-terminated movements, has been controversial. Computer simulations show that the pattern emerges from interactions between a central neural trajectory controller (VITE circuit) and a peripheral neuromuscular force controller (FLETE circuit). Both neural models have been derived from simple functional constraints that have led to principled explanations of a wide variety of behavioral and neurobiological data, including the generation of tri-phasic bursts. [8]

(7C) Cerebellar learning in an opponent motor controller for adaptive load compensation and synergy formation

A minimal neural network model of the cerebellum is embedded within a sensory-neuromuscular control system that mimics known anatomy and physiology. With this embedding, cerebellar learning promotes load compensation while also allowing both coactivation and reciprocal inhibition of sets of antagonistic muscles. In particular, we show how synaptic long term depression guided by feedback from muscle stretch receptors can lead to transcerebellar gain changes that are load-compensating. It is argued that the same processes help to adaptively discover multi-joint synergies. Simulations of rapid single joint rotations under load illustrates design feasibility and stability. [7]

(7D) Optimal control of machine set-up scheduling

An optimal control solution to change of machine set-up scheduling is demonstrated. The model is based on dynamic programming average cost per stage value iteration as set forth by Caramanis *et al.* for the 2-D case. The difficulty with the optimal approach lies in the explosive computational growth of the resulting solution. A method of reducing the computational complexity is developed using ideas from biology and neural networks. A real-time controller is described that uses a linear-log representation of state space, with neural networks employed to fit cost surfaces. [2]

(7E) Vector associative maps: Unsupervised real-time error-based learning and control of movement trajectories

This project has led to the development of neural network models for adaptive control of arm movement trajectories during visually guided reaching and, more generally, a framework for unsupervised real-time error-based learning. The models clarify how a child, or untrained robot, can learn to reach for objects that it sees. It is shown how endogenously generated arm movements lead to adaptive tuning of arm control parameters. These movements also activate the target position representations that are used to learn the visuo-motor transformation that controls visually guided reaching. The AVITE model is an adaptive neural circuit based on the Vector Integration to Endpoint (VITE) model for arm and speech trajectory generation of Bullock and Grossberg. In the VITE model, a Target Position Command (TPC) represents the location of the desired target. The Present Position Command (PPC) encodes the present hand-arm configuration. The AVITE model explains how self-consistent TPC and PPC coordinates are autonomously generated and learned. Learning of AVITE parameters is regulated by activation of a self-regulating Endogenous Random Generator (ERG) of training vectors. Each vector is integrated at the PPC, giving rise to a movement command. The generation of each vector induces a complementary postural phase during which ERG output stops and learning occurs. ERG output autonomously stops in such a way that, across trials, a broad sample of workspace target positions is generated. Learning of a transformation from TPC to PPC occurs using the DV as an error signal that is zeroed due to learning. This learning scheme is called a Vector Associative Map, or VAM. The VAM model is a general-purpose device for autonomous real-time error-based learning and performance of associative maps. VAMs thus provide an on-line unsupervised alternative to the off-line properties of supervised error-correction learning algorithms. VAM models and Adaptive Resonance Theory (ART) models exhibit complementary matching, learning, and performance properties that together provide a foundation for designing a total sensory-cognitive and cognitive-motor autonomous system. [49–52]

(7F) A neural pattern generator that exhibits bimanual coordination and human and quadruped gait transitions

A neural pattern generator is based upon a nonlinear cooperative-competitive feedback neural network. The system can generate two standard human gaits: the walk and the run. A scalar arousal or GO signal causes a bifurcation from one gait to the next. Although these two gaits are qualitatively different, they both have the same limb order and may exhibit oscillation frequencies that overlap. The model simulates the walk and the run via qualitatively different waveform shapes. The fraction of cycle that activity is above threshold distinguishes the two gaits, much as the duty cycles of the feet are longer in the walk than in the run. The two-channel version of the model simulates data from human bimanual coordination tasks in which anti-phase oscillations at low frequencies spontaneously switch to in-phase oscillations at high frequencies, in-phase oscillations can be performed at both low and high frequencies, phase fluctuations occur at the anti-phase to in-phase transitions, and a "seagull effect" of larger errors occurs at intermediate phases. In a four-channel neural pattern generator, both the frequency and the relative phase of oscillations are controlled by scalar arousal. The generator is used to simulate quadruped gaits: in particular, rapid transitions are simulated in the order—walk, trot, pace, and gallop—that occurs in the cat. Precise switching control is achieved by using an arousal dependent modulation of the model's inhibitory interactions. This modulation generates a different functional connectivity in a single network at different arousal levels. [40–43]

(7G) VITEWRITE: A neural network model for handwriting production

A neural network model called VITEWRITE is shown to generate handwriting movements. The model consists of a sequential controller, or motor program, that interacts with a trajectory generator to move a hand with redundant degrees of freedom. The neural trajectory generator is the Vector Integration to Endpoint (VITE) model for synchronous variable-speed control of multijoint movements. VITE properties enable a simple control strategy to generate complex handwritten script if the hand model contains redundant degrees of freedom. The proposed controller launches transient directional commands to independent hand synergies at times when the hand begins to move, or when a velocity peak in a given synergy is achieved. The VITE model translates these temporally disjoint synergy commands into smooth curvilinear trajectories among temporally overlapping synergetic movements. The separate "score" of onset times used in most prior models is hereby replaced by a self-scaling activity-released "motor program" that uses few memory resources, enables each synergy to exhibit a unimodel velocity profile during any stroke, generates letters that are invariant under speed and size rescaling, and enables effortless connection of letter shapes into words. Speed and size rescaling are achieved by scalar GO and GRO signals that express computationally simple volitional commands. Psychophysical data concerning hand movements, such as the isochrony principle, asymmetric velocity profiles, and the two-thirds power law relating movement curvature and velocity arise as emergent properties of model interactions. [9-10]